The Internal Structure of Cities:

Koster, H.R.A.

2013

2 Agglomeration economies and productivity: A structural estimation approach using commercial rents[*]

2.1 Introduction

The seminal paper by Ciccone and Hall (1996) provides clear evidence that spatial density results in aggregate increasing returns. A large literature confirms the relationship between productivity and economic density (see Melo et al., 2009 for a meta-analysis), and shows that this relationship also holds for different industries, different levels of aggregation and different countries and cities (see e.g. Ciccone, 2002; Brülhart and Mathys, 2007; Combes et al., 2010; Morikawa, 2011). Agglomeration of economic activities may benefit firms and increase productivity due to labour market pooling, input sharing and knowledge spillovers (Marshall, 1920). Rosenthal and Strange (2004) argue that wages, high productivity employment and rents reflect the presence of agglomeration economies. Very few studies use rents to measure the magnitude of external economies, although it has been shown that agglomeration effects mainly capitalise in rents (Arzaghi and Henderson, 2008; Drennan and Kelly, 2011). Furthermore, urban economics usually focuses on the manufacturing sector, while we may expect that there are substantial differences in the magnitude of agglomeration economies between different sectors (Eberts and McMillen, 1999; Drennan and Kelly, 2011). For example, retailers are likely to prefer relatively dense areas with many shops in the vicinity, as customers may go to a shop nearby as well (Eberts and McMillen, 1999).

In this chapter we use detailed firm-level data that enables us to investigate the heterogeneity in the productivity of agglomeration economies across different industries.[4] More specifically, we use commercial rents and employ a structural estimation approach. We show how estimated *firm-specific* WTP-elasticities are linked to structural parameters of the production function, which has agglomeration and property size among its arguments, following Bajari and Benkard (2005) and Bajari and Kahn (2005).[5] A problem is that in contrast to a market of household demand for consumer goods (like housing), the assumption of a linear utility function, which is needed for identification in a single market, is inappropriate for producers because for most industries firms substitute between different inputs implying a nonlinear production function. However, we demonstrate that one can identify useful information about the firm-specific production function that allows for input factor substitution. It is

---

* This chapter is based on Koster, H.R.A., Van Ommeren, J.N., Rietveld, P. (2013). Agglomeration Economies and Productivity: A Structural Estimation Approach Using Commercial Rents. *Forthcoming in Economica*. NVM (Dutch Association of Real Estate Agents), WDM and the Rijksmonumentenregister are gratefully acknowledged for providing data. This chapter has been presented at the 1st European Meeting of the Urban Economics Association, at the KUHMO-Nectar Conference 2010 and at the Erasmus University Rotterdam. Seminar audiences are thanked for their constructive comments. We also thank the editor of Economica, Alex Michaelides, and an anonymous referee for comments.

4 We also pay specific attention to the willingness to pay for size of the rental property. This is of particular interest because of the presence of internal returns to scale in terms of employment (Coase, 1937; Tybout, 1993). As employment and size of the rental property are complementary in the production function, larger firms are thought to differ in their willingness to pay more for an additional square meter compared to smaller firms.

5 Analysing underlying structural parameters is of obvious interest, as there is no reason to assume that the marginal willingness to pay for a specific attribute also holds in different markets and different time periods.

shown that given a firm-specific generalised Cobb-Douglas production function, the ratios of structural parameters of rental property attributes of interest can be identified.

We aim to investigate producer heterogeneity in agglomeration economies. We will focus on the firm-specific parameter of agglomeration relative to its parameter of floor space. So, we are able to estimate structural (firm-specific) ratios of agglomeration and floor space parameters. These ratios are useful as they indicate how much each firm spends on agglomeration relative to their expenditure on floor space, which is an intuitive measure. To investigate heterogeneity, we regress the estimated ratios on firms' sector and workforce size, which are arguably the most important firm characteristics regarding property demand, and show how relative expenditure on agglomeration varies among firms.

We use a unique new dataset that provides micro information on property attributes, as well as firm characteristics. To our knowledge, this is the first dataset that provides information on commercial transactions *and* tenants. Furthermore, we have data not only on office transactions, but also on transactions of industrial buildings and shops. We use an agglomeration metric that is continuous over space to avoid the arbitrariness in the choice of spatial units. A two-stage hedonic price approach is employed that allows for endogeneity of the agglomeration measure, given appropriate instruments.[6] In the first stage, we estimate a semiparametric hedonic price function of property attributes using techniques that control for the endogeneity of agglomeration. This approach, advocated by Newey et al. (1999) and Blundell and Powell (2003), is not much applied yet in empirical literature. In the second stage, we identify firm-specific ratios of production function parameters and regress these on firm characteristics.

Results show that agglomeration has a statistically significant effect on rents: doubling of agglomeration leads to an increase in rents of about 3.5 percent. Expenditure on agglomeration is however rather limited: it is on average about 5.3 percent of the expenditure on office space. Nevertheless, there is a lot of heterogeneity in the factor shares related to agglomeration. For example, expenditure on agglomeration relative to expenditure on space is about 20 percent for retailers.

This chapter proceeds as follows. In Section 2.2, we discuss the literature concerning identification and estimation of hedonic price model and elabourate on the advantages and disadvantages of our approach. We then outline a model where we derive the necessary conditions that enable identification of ratios of production function parameters. This is followed by a discussion on the empirical estimation strategy in Section 2.3. Section 2.4 discusses the data and regional context. Section 2.5 presents the results for the parametric models. In Section 2.6, we consider the results of the semiparametric estimation procedure and provide an analysis of the (ratios of) structural parameters of the production functions. Section 2.7 concludes and derives some policy implications.

---

[6] We use commercial rents to investigate the magnitude of agglomeration externalities. As we make a comparison between different sectors, this is more appropriate than the use of total factor productivity or value added. These indicators often suffer from biases and are difficult to compare across industries (see e.g. Morikawa, 2011).

2.2 A hedonic price approach

A. Identification and estimation of hedonic price models

This chapter contributes to an emerging literature on the identification of nonparametric hedonic models in single markets. To identify structural parameters in hedonic models, Rosen (1974) suggested a two-step procedure. In step one, one has to estimate the marginal willingness to pay for a certain attribute. In step two, the estimated marginal WTP is used in conjunction with first-order conditions of attributes. However, it may be shown that technology parameters are only identified given arbitrary functional form assumptions, e.g. assuming that there are homogeneous firms or consumers (see for a more detailed discussion Ekeland et al, 2002 and Bajari and Benkard, 2005). Importantly, and surprisingly, Ekeland et al. (2004) show that the marginal WTP is almost certainly a nonlinear function of the attribute of interest. Ekeland et al. (2004) furthermore show that this nonlinearity provides information that rules out collinearity between an endogenously-chosen attribute and its marginal willingness to pay. This enables identification of structural parameters in a single market, given the assumption that unobserved characteristics (e.g. of firms) are independent of observed characteristics and marginal utility is additive. Heckman et al. (2010) extend this approach, by considering identification in nonadditive hedonic models (so, interactions between observable and unobservable (firm) characteristics are allowed). However, Ekeland et al. (2002; 2004) and Heckman et al. (2004) focus on single-dimensional hedonic models (so with a single attribute or a single index structure, as in Epple and Sieg (1999) and Sieg et al. (2004)). This limits the applicability to commercial property markets, as commercial properties are functions of many attributes, which are difficult to summarise in a single index. Our approach is essentially an adaptation of Bajari and Benkard (2005) and Bajari and Kahn (2005), who consider identification of structural parameters in a multidimensional hedonic price model in presence of consumer heterogeneity. They show that, given a linear utility function, structural parameters are identified, as well as the willingness to pay for an unobserved attribute.[7] To apply this idea to identify structural parameters given producer heterogeneity is not possible, because for most industries, firm production functions are not linear as firms substitute between different inputs (land, capital, rental property attributes) in order to maximise profits.

We therefore consider the question which parameters of interest can be identified given production functions that allow for flexible input factor substitution between rental property attributes (e.g. office space) and other inputs (e.g. labour). We show that given a generalised Cobb-Douglas production function that is unique for each firm, the ratios of structural parameters of rental property attributes of interest can be identified. In our empirical application, we are able to estimate the ratios of agglomeration and office space parameters. These ratios are useful as they indicate how much each firm spends on agglomeration relative to their expenditure on office space.

Our structural estimation approach has three advantages. First, the required functional form assumptions on the economies of scale of the production function are weak. It allows for constant, decreasing as well as increasing returns to scale in production. Second, it allows for flexible substitution between rental property attributes and other inputs of the production function. Third, multi-

[7] For identification of *firm-specific parameters*, assumptions on the utility/production function are inevitable, given cross-sectional data. These can be relaxed in a panel-data setting (see Bishop and Timmins, 2008).

dimensional hedonic models with many attributes and firm characteristics can be analysed in a single market. There are however also limitations of the current approach. The factor substitution between rental property attributes is constrained to be such that the elasticity of substitution is one and we cannot identify absolute levels of production function parameters; we have to rely on ratios of two structural parameters.

B. An empirical model for the commercial property market

Firms are assumed to maximise profit subject to a production function in a perfectly competitive market (see also Palmquist, 1988; Bollinger et al., 1998). In order to produce, firms need to rent buildings, and for convenience we assume a perfectly competitive property market, so prices are given. Let π_i denote the profit of firm i in property j, p_j is the location-specific price of output y_{ij} in j, c denotes the price of input x_i, $i = 1, \ldots, I$ and $j = 1, \ldots, J$. We suppose that the paid rent R_{ij} by firm i for property j is some function of employment density a, size of the rental property s and another attribute of the rental property z. Output y_{ij} is a continuous function Φ_i of rental property attributes and other inputs. Hence, conditional on the choice of property j and therefore conditional on the rental property attributes, firm behaviour is characterised by maximising profits with respect to non-building inputs x_i and rental property attributes:

(2.1) $$\max \pi_{ij} = p_j - cx_i - R_{ij}(a_j, s_j, z_j),$$

subject to $y_{ij} = \Phi_i(x_i, a_j, s_j, z_j)$. Given rental property attributes, price p_j and c, this maximisation problem solves for non-building input $x_i^* = x(p_j, c, a_j, s_j, z_j)$. Then, the perfectly competitive market assumption for firms ensures that:

(2.2) $$p_j \Phi_i(x_i^*, a_j, s_j, z_j) - cx_i^* - R_{ij}(a_j, s_j, z_j) = 0.$$

So, equation (2.2) defines the bid rent of firm i for property j. To obtain the partial derivative of the equilibrium rent R_{ij} with respect to variable a_j, we take first derivatives. Using the envelope theorem, we arrive at the following condition:

(2.3) $$\frac{\partial R_{ij}}{\partial a_j} = p_j \frac{\partial \Phi_i}{\partial a_j}.$$

This condition is intuitive, as $p_j \Phi_i(\cdot)$ denotes revenue. It states that the marginal effect of a rental property attribute on the rent is equal to its marginal effect on the revenue function (the production function multiplied with the output price).

As we have only one observation per firm, we have to make functional form assumptions in order to be able to identify parameters of the production function. In what follows, we assume a standard double-log hedonic price function:

(2.4) $$\log R_{ij} = \beta_i \log a_j + \gamma_i \log s_j + \delta_i \log z_j.$$

where β, γ, δ are parameters to be estimated empirically. Hence, for an attribute, let's say agglomeration, it holds that $\partial R_{ij}/\partial a_j = \beta_i R_{ij}/a_j$.[8] Although (2.4) seems a restrictive functional form,

[8] Given a generalised Cobb-Douglas production function, for identification no particular functional form of the hedonic price function is required. We assume a firm-specific double-log hedonic price function to overcome the curse of multidimensionality, common in nonparametric estimation procedures.

note that the coefficients to be estimated are firm-specific. So, over the full population, this will lead to nonparametric distributions of WTP-coefficients.

Similar to Bajari and Kahn (2005), we make assumptions on the production function, in order to identify ratios of parameters of the production function. We consider a generalised Cobb-Douglas production function in x_i, a_j, s_j and z_j:

$$\Phi_i\left(x_i^*, a_j, s_j, z_j\right) = m\left(n(x_i) a_j^{\mathrm{B}_i} s_j^{\Gamma_i} z_j^{\Delta_i}\right), \tag{2.5}$$

where Β, Γ and Δ are firm-specific parameters of the production function, $m(\cdot)$ and $n(\cdot)$ are unspecified functions.[9]

Let us now consider identification. For example, for agglomeration a_j we have $\beta_i R_{ij} = p_j \mathrm{B}_i m'(\cdot) n(x_i) a_j^{\mathrm{B}_i} s_j^{\Gamma_i} z_j^{\Delta_i}$, given (2.3), (2.4) and (2.5). It is immediately observed that one cannot identify B_i given cross-sectional data. However, it is straightforward to see that the ratio of derivatives of the rent function with respect to two property attributes, let's say a_j and s_j, is the same as the ratio of the related structural parameters of the production function. Using (2.3), (2.4) and (2.5), it holds that:

$$\frac{\beta_i}{\gamma_i} = \frac{\mathrm{B}_i}{\Gamma_i}. \tag{2.6}$$

So, we are able to identify ratios of structural parameters, which provides us with information on the relative productivity of a rental property attribute. This information is useful, because a well-known property of the Cobb-Douglas function is that the ratio of Cobb-Douglas input parameters is equal to the ratio of expenditures on corresponding input variables (Varian, 2010, pp. 35). In our application, we will focus on two input factors: agglomeration and floor space. So, for example, for office buildings, we are able to estimate how much firms spend on agglomeration relative to expenditure on office floor space.

2.3 Estimation procedure

A. First stage

We estimate the implicit prices faced by firm i that occupies property j. To control for unobserved heterogeneity we add M dummies v_m (e.g. transaction year dummies and municipality fixed effects) to our specification, where $m = 1, \dots, M$.[10] We also include interactions of the size of the rental property with building type t (office, shop, industrial building) because the unobserved quality of an additional square meter is highly correlated with building type, where $t = 1, \dots, T$ and other attributes z_k, where $1, \dots, K$.[11] To reduce the number of nonparametric parameters in the function to be estimated, we assume that the latter dummies are linearly related to the rent. This reduces the curse of

[9] One alternative to the generalised Cobb-Douglas production function is the linear perfect substitutes production function, which enables one to identify *absolute* levels of the structural parameters. However, such a production function implies assumptions that are hard to defend in the current context (e.g. because it does not allow for input substitution).

[10] Including fixed effects at a lower spatial level would make the computational procedure too demanding and identification of (local) agglomeration effects too difficult.

[11] For example, office space refers to a much higher quality building, in particularly internally, whereas industrial buildings are usually bare.

multidimensionality, a limitation of nonparametric applications (Yatchew, 2003). We then have the following rent function:

$$\log R_{ij} = \Omega_i\left(\log a_j, I_{1j}\log s_{1j}, \ldots, I_{Tj}\log s_{Tj}, \log z_{1j}, \ldots, \log z_{Kj}\right) + \sum_{m=1}^{M} \eta_m v_{mj} + \xi_j, \tag{2.7}$$

where η are parameters to be estimated and ξ_j denotes the property-specific error term and I_{tj} is indicator function that equals one when $s_{tj} > 0$.[12] We employ an estimation approach proposed by Fan and Gijbels (1996). $\Omega_i(\cdot)$ is then estimated using locally weighted regression. Locally weighted regression is the most common nonparametric approach to analyse spatial data, as it allows for a flexible functional form and interactions between the variables of interest.[13] Because we use local linear regression techniques, we may write $\Omega_i(\cdot) = \beta_i \log a_j + \sum_{t=1}^{T} \gamma_{ti} I_{tj} \log s_{tj} + \sum_{k=1}^{K} \delta_{ki} \log z_{kj}$. Note that the coefficients β_i, γ_{ti} and δ_{ki} are firm-specific. So, local linear regression implies that one estimates for each firm a weighted regression based on a multivariate kernel using g firm characteristics, where $g = 1, \ldots, G$:

$$w_{i\ell} = \prod_{g=1}^{G} k_{i\ell g}(h_g; f_{\ell g} - f_{ig}), \tag{2.8}$$

where w is the kernel weight of ℓ in the local regression of i and $k_g(\cdot)$ is a kernel function of a chosen bandwidth h_g and the difference between the firm characteristics f_{ig} and $f_{\ell g}$. Note that when firms have exactly the same (observable) characteristics, they are assumed to have the same preferences, i.e. we estimate for each unique firm type a weighted regression. Most studies use the same kernel function $k_g(\cdot)$ for all variables. However, Racine et al. (2006) showed that the use of different kernel functions for continuous and categorical variables is required. For continuous firm characteristics we use a conventional Gaussian kernel function:

$$k_{i\ell g} = \frac{1}{h_g\sqrt{2\pi}} \mathrm{e}^{-\frac{1}{2}\left(\frac{f_{\ell g} - f_{ig}}{h_g}\right)^2}. \tag{2.9}$$

For categorical firm characteristics we employ the following kernel function (see Racine and Li, 2004; Racine et al., 2006):

$$k_{i\ell g} = \begin{cases} 1 & \text{if } f_{\ell g} = f_{ig} \\ h_g & \text{if } f_{\ell g} \neq f_{ig} \end{cases}. \tag{2.10}$$

An important parameter of the kernel functions (2.9) and (2.10) are the bandwidths h_g. A lower bandwidth leads to a lower mean-squared error, but to higher variance of the estimator. A larger bandwidth may create a larger bias when the underlying function is nonlinear (Fan and Gijbels, 1996). We employ a bandwidth of 1.5 and 0.3 for respectively continuous and categorical firm characteristics.

---

[12] Bajari and Kahn (2005) interpret ξ_j as an unobserved product characteristic. As we include municipality fixed effects, year dummies and employ a control function approach to estimate (7), to be discussed later on, ξ_j represents an approximation error in our analysis.

[13] In the hedonic price literature, local linear techniques are often applied, where parameters are estimated that depend on geographic location (also known as geographically weighted regression) (McMillen and Redfearn, 2010). We let the parameters depend on firm characteristics. This is in contrast to Bajari and Kahn (2005), who include all explanatory variables in the kernel.

Lower bandwidths lead to nearly singular weight matrices for a number of observations, which in turn lead to unreliable estimates.[14]

There are two main issues in our set-up that complicate the estimation procedure. First, as equation (2.7) is partially linear, we employ the Robinson procedure (Robinson, 1988). We then regress $\log R_{ij}$ and v_{mj} on ($\log a_j, I_{1j} \log s_{1j}, \dots, I_{Tj} \log s_{Tj}, \log z_{1j}, \dots, \log z_{Kj}$) nonparametrically. The following step is to regress the residuals of $\log R_{ij}$ on the residuals of v_{mj}. This leads to $\sqrt{N}$-consistent estimates for η_m. Robinson showed that the coefficients are estimated at parametric rates of convergence, despite the presence of a nonparametric part. The last step is to regress $\log R_{ij} - \sum_{m=1}^{M} \hat{\eta}_m v_{mj}$ nonparametrically on $\log a_j, I_{1j} \log s_{1j}, \dots, I_{Tj} \log s_{Tj}, \log z_{1j}, \dots, \log z_{Kj}$ to get an estimate for $\Omega_i(\cdot)$.

A second issue is the endogeneity of agglomeration. To account for this, we employ a control function approach (see Blundell and Powell, 2003; Yatchew, 2003). This approach treats endogeneity as an omitted variable problem, comparable to Heckman's correction for selectivity bias, through the introduction of an appropriately estimated control function (Heckman, 1979). An important restrictive assumption of the control function approach is that the endogenous variable must be continuously distributed, which is fulfilled in our application. Given the use of local linear models, this approach is preferred to two main alternative approaches to correct for endogeneity such as IV and plugging in fitted values (Blundell and Powell, 2003).[15] The procedure to apply the control function is to first regress the endogenous independent variable on all exogenous independent variables and instruments (to be discussed in Section 2.4.B).[16] The predicted errors of this step are used as a nonparametric control function which is additive to the dependent variable in the second step. This solves the inconsistency of standard nonparametric estimation (Newey et al., 1999; Pinkse, 2000).

B. Second stage

In the second stage, we identify the ratios of parameters of the production function (defined by (2.5)) of a firm. We regress ratios of structural parameters on firm characteristics:

$$\frac{\mathrm{B}_i}{\Gamma_{ti}} = \sum_{g=1}^{G} \theta_g f_{ig} + \omega_i, \tag{2.11}$$

where θ_g are parameters to be estimated and ω_i denotes an error term. We estimate this model for all t. Note that we use a linear model. We may use flexible estimation techniques, but for presentation

---

[14] Conventional bandwidth selection methods, such as minimising the Akaike Information Criterion, Generalised Cross Validation (see Hurvich et al., 1998) and the T-value of Rice (1984) lead to oversmoothing and less variation in the coefficients, whereas Silverman's rule of thumb and the Zheng rule lead to undersmoothing and unreliable estimates (see Silverman, 1986; Bishop and Timmins, 2008).

[15] Note that in (global) linear models, the control function approach, instrumental variables, and plugging in fitted values in the second stage will lead to the same results. This is not the case in nonlinear and nonparametric models. Newey and Powell (2003) propose a nonparametric two-step least squares estimator (NP2SLS), which is applicable to series approximation (such as polynomials) but not to local linear methods, as we use in our work. As is well known, the intuitive approach to plug fitted values of the first stage into the second stage leads to inconsistent estimates of nonlinear and nonparametric parameters (Ameniya, 1974; Angrist and Pischke, 2009).

[16] So, we estimate the following equation: $\log a_j = \Psi_i\left(q_{1j}, q_{2j}, I_{1j} \log s_{1j}, \dots, I_{Tj} \log s_{Tj}, \log z_{1j}, \dots, \log z_{Kj}\right) + \sum_{m=1}^{M} \kappa_m v_{mj} + \mu_j$, where κ are parameters to be estimated and $\Psi_i(\cdot)$ is some function of instruments q, rental property size s and other attributes$z$.

purposes it is more convenient to assume a linear relationship between firm characteristics and the estimated ratios of structural parameters (see similarly Bajari and Kahn, 2005). This enables us to determine which type of firms will be relatively more productive in dense urban areas.

2.4 Data

A. Datasets

We use three datasets. The first consists of transactions of commercial properties provided by real estate agents between 1990 and 2010 in the NUTS3-region South-Holland, located in the west of the Netherlands. This region includes Rotterdam, the second largest city of the Netherlands, and The Hague, where the national government is located, but also cities such as Leiden and Gouda. This region covers about 20 percent of national economic activity. The dataset contains information about annual rent and rental property attributes, such as address, size (gross floor area in square meters), type of building (e.g. shop, office), number of parking spaces and whether the building is newly constructed or renovated. We also have information on the rental contracts, such as whether the office is rented turnkey and whether there is a sale-and-lease-back construction.[17] The data also provide the name of the firm that occupies the building. After selections, the dataset consists of 2,631 transactions.[18]

In the analysis, we focus on the effects of agglomeration and size of the rental property, controlling for a range of locational attributes.[19] First, we add 56 municipality fixed effects, so we have on average 47 observations per municipality. Besides these fixed effects, we include dummy indicators whether a property is within 150 meters of a road, a highway, a railway, open space or water and within 250 meters of the nearest railway station. We also verify whether the rental property is in a building that is taller than 80 meters, as such buildings are often landmarks that offer amenities to its tenants (see Helsley and Strange, 2008; see also Chapter 4). We furthermore investigate whether an office building is listed and is in a conservation area, using a dataset from the *Rijksmonumentenregister* (Listed Building Register).

Our second dataset contains information about characteristics of *all* establishments in the South-Holland region in 2005. This information comes from administrative sources and is very reliable, as Dutch firms are obliged by law to provide this information. We have information on the establishment's exact location, SBI five-digit sector and number of employees.[20] For the semiparametric regressions, the latter two variables are relevant to include in the multivariate kernel (see equation (2.8)).[21] We match

---

[17] A turnkey office is rented in a ready-to-use condition, including carpets, office furniture, etc.

[18] When firms rent a part of a building, the rent and attributes of the transaction refer to the rental property (the rented part of the building). We exclude observations that do not provide information about the building's size or rent, or which refer to properties smaller than 20 square meter, larger than 20,000 square meter or with yearly rents above € 2,500,000 or below € 5,000 and a square meter price above € 1,000 or below € 25.

[19] Eichholtz et al. (2010) argue that there are three approaches to correct for spatial variation in prices. First, by including dummies for each submarket. Second, by focusing on a specific city or metropolitan area and third, by including locational variables such as distance to railway stations etc. We combine those approaches: we focus on a particular area (South-Holland), include location dummies *and* control for a wide range of locational attributes.

[20] SBI (*Standaard Bedrijfsindeling*) is a Dutch variant of the Standard Industrial Classification.

[21] More specifically, we include a continuous variable employment and four categorical variables in the kernel: the SBI main sector, the SBI two-digit sector, SBI three-digit sector and SBI five-digit sector. This implies that firms in

the information on establishment's name. Note that we match data from 2005 with building transaction data from 1990-2010. Therefore, the number of employees may not be entirely correct. Nevertheless, as most buildings are of a given size, establishments usually move when the number of employees changes substantially, so the measurement error is likely not substantial.[22] In the remainder of this chapter, we label establishments as firms and usually refer to rents as prices.

Central to our analysis is the effect of spatial density. Following scholars such as Fujita and Ogawa (1982), Helsley (1990) and Lucas and Rossi-Hansberg (2002), who argue that workers are more productive when they are employed in the vicinity of other workers, agglomeration is measured by a weighted average of the number of jobs located in the neighbourhood of the property using a decay function that is continuous over space.[23] The use of a continuous metric is preferred, as to avoid problems inherent to arbitrary spatial units (see Briant et al., 2010 for a discussion). Formally:

$$a_j = \int_k l_{jk}\, n_k \mathrm{d}k, \tag{2.12}$$

where n_k denotes the number of workers in property k, where $k \neq j$, so we do not take into account the own employment to avoid biases. Note that the weight is estimated using a tricube weighting function, which is often used in spatial applications (see McMillen, 2010):

$$l_{jk} = \left(1 - \left(\frac{d_{jk}}{d_T}\right)^3\right)^3 I(d_{jk} < d_T) \tag{2.13}$$

where d_{jk} is the distance between location j and k and d_T is a threshold distance and $I(\cdot)$ is an indicator function that equals one when $d_{jk} < d_T$. We choose $d_T = 2.5$, so employment that is located further away than 2.5 kilometres does not influence a_j, so agglomeration is measured rather locally. For example, given a uniform distribution of employment over space, about 90 percent of the weight of this measure is within 1.5 kilometres of the location. A map of the pattern of agglomeration is presented in Figure A1 in the Appendix. It is confirmed that Rotterdam and The Hague are the main employment centres. Other employment concentrations are found in university cities Leiden and Delft and other medium-sized cities, such as Zoetermeer, Dordrecht and Gouda.

Descriptive statistics for the rental transaction are presented in Table 2.A1 and for firm characteristics in Table 2.A2 in the Appendix. The yearly rent is on average € 131,085 and the standard deviation is quite substantial (€ 207,563). About 60 percent of the transactions refer to office transactions, 25 percent to shops and 15 percent to industrial buildings. Office buildings are on average the largest (1,075 square meter). Most firms in our dataset are business services (38 percent), followed

---

the same five-digit sector will have more similar WTP-coefficients than, for example, firms in the same two-digit sector.

[22] It is assumed that workforce size and industry are exogenous. One may however argue that the size of the workforce of a firm is endogenous. For example, firms that for unobserved reasons prefer larger more prestigious buildings may hire more workers. However, these endogenous changes in workforce size should be minimal compared to the large differences in workforce size between firms.

[23] We focus on the returns to employment density. It appears that our dataset is too small to identify sector-specific localisation economies, as we find high correlations between within-sector clustering and between-sector clustering. Moreover, we would have two endogenous variables and our instruments are then *locally* not strong enough. We leave the possibility to separate localisation and urbanisation effects for studies that have more observations.

by retailers and wholesalers (respectively 20 and 14 percent). The average square meter per employee is 17.58, which is very similar to the national average (see NFC, 2010). The average firm size is equal to 67, which is much higher than the regional average of 12 employees per firm. However, in the full dataset with all firms, there are many firms with zero or one employee. These are often entrepreneurs that work from home or holdings that do not occupy commercial buildings.

B. Endogeneity of agglomeration

As argued by Bayer and Timmins (2007), among others, location decisions alone are insufficient in distinguishing the potential of local spillovers from those of local locational advantages. As a result, any positive effect of agglomeration is likely to be overstated (Ellison and Glaeser, 1999; Bayer and Timmins, 2007). We therefore need an instrument which is correlated with agglomeration but uncorrelated with any unobserved locational advantage. We use population density of *municipalities in 1870* as an instrument for agglomeration. Note that municipalities in 1870 were much smaller and do not overlap with current ones. South-Holland, the region which our data refer to, consisted in 1870 of 213 municipalities, whereas nowadays it consists of only 77 municipalities. The instrument's validity rests on the assumption that population density in 1870 is unrelated to current locational advantages (and therefore profit of firms), but has a causal effect on the current agglomeration pattern (see also Ciccone and Hall, 1996; Rice et al., 2006; Combes et al., 2008). This instrument is strong as population density is strongly autocorrelated and (current) population and employment densities are positively correlated (McMillen and McDonald, 1998). However, given that one observes extreme persistence of location patterns over time, it may well be that unobserved endowments that were important a century ago are still an important determinant of current rents. In Chapter 3 we will pay more attention to identification of agglomeration economies and show that an approach using historic instruments seems to consistently identify the effect of agglomeration economies.

The second instrument follows a similar logic as historic population density instrument. We include the distance to the nearest station in 1870. Stations were an important factor that caused agglomeration in the second half of the 19th century (Ciccone and Hall, 1996). Locations nearby stations were therefore likely to attract more businesses. The current lay-out of the railroad network differs substantially from that in 1870 and we condition on locations that are close to current railway stations. It is therefore unlikely that the distance to the nearest station in 1870 has an impact on current rents.

2.5 Parametric regressions

A. Results

Table 2.1 presents the results of fully parametric regressions based on equation (2.7). This implies that $\Omega_i(\cdot) = \beta \log a_j + \sum_{t=1}^{T} \gamma_t I_{tj} \log s_{tj} + \sum_{k=1}^{K} \delta_k \log z_{kj}$, so we provisionally assume that there is no heterogeneity in the WTP-parameters. Specification (1) is an ordinary least squares regression of rents on agglomeration, size of the rental property and a large number of control variables. The agglomeration elasticity is 0.082. The elasticities of size with respect to rent differ for different building types, as expected. Especially the elasticity of size in shops is relatively low. As the marginal willingness

TABLE 2.1 — PARAMETRIC REGRESSION RESULTS
(Dependent variable: the logarithm of yearly rent)

	(1)	(2)
Agglomeration *(log)*	0.082 (0.012)***	0.051 (0.014)***
Size office *(log)*	0.998 (0.007)***	1.000 (0.006)***
Size shop *(log)*	0.644 (0.022)***	0.646 (0.021)***
Size industrial building *(log)*	0.890 (0.020)***	0.887 (0.020)***
Shop	2.474 (0.127)***	2.475 (0.125)***
Industrial building	0.046 (0.155)	0.057 (0.152)
Renovated building	0.069 (0.037)*	0.074 (0.037)**
Newly constructed building	0.154 (0.018)***	0.148 (0.018)***
Building height >80m	0.121 (0.040)***	0.142 (0.040)***
Listed building	-0.087 (0.043)**	-0.086 (0.042)**
Sale and lease back	0.096 (0.064)	0.099 (0.065)
Rent turnkey	0.057 (0.035)	0.057 (0.034)*
Parking spaces *(log)*	0.073 (0.016)***	0.070 (0.016)***
Parking spaces – missing	-0.202 (0.027)***	-0.203 (0.026)***
Road <150m	-0.003 (0.018)	-0.003 (0.018)
Highway <150m	0.122 (0.020)***	0.114 (0.020)***
Railway <150m	-0.016 (0.019)	-0.019 (0.019)
Open space <150m	0.035 (0.017)**	0.022 (0.017)
Water <150m	-0.037 (0.014)***	-0.040 (0.013)***
Station <250m	0.029 (0.031)	0.040 (0.030)
Conservation area	0.098 (0.025)***	0.115 (0.025)***
Municipality fixed effects (56)	Yes	Yes
Transaction year dummies (20)	Yes	Yes
Number of observations	2,631	2,631
R^2	0.906	
F-Test for weak instruments		1,772.630
Test for exogeneity (critical value)		11.575 (3.841)
Overidentification test (critical value)		2.000 (3.841)

Notes: Instruments in Specification (2) are the logarithm of population density in 1870 and the distance to the nearest station in 1870. The test for exogeneity and the overidentification test are robust χ^2-scores. The robust standard errors are between parentheses.
*** Significant at the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

to pay for an additional square meter is lower in shops, we may expect that shops are smaller than offices and industrial buildings, which is indeed the case: in our sample the average size of shops is only 37 percent of the average size of offices.

In Specification (2) we use instrumental variables to estimate the effect of agglomeration (as measured by the weighted employment density). As instruments we include the log of population density in 1870 and the distance to the nearest station in 1870. It is observed that these instruments are strong (the F-value is 1,773). The elasticity of agglomeration is somewhat lower and 0.051, suggesting that the estimate obtained from Specification (1) is biased upwards. This is plausible, as employment density is likely correlated with unobserved natural advantages. Doubling of agglomeration then leads to an increase in rents of 3.5 percent.[24] We do find evidence that agglomeration is endogenous. The value of a Hausman exogeneity test is 11.575, which is much higher than the 5 percent critical value of

[24] This is calculated as follows: $\log(2) \cdot 0.051 = 0.035$

3.841. The over-identification test is not significant (the test value is 2, which is lower than the critical value of 3.841), suggesting that the instruments are not correlated with the error term. The elasticities related to the size of the rental property are hardly affected. Given these estimates and assuming homogeneous firms, we may calculate the ratio of structural parameters for agglomeration and size of the rental property. The estimated expenditure on agglomeration relative to floor space is limited: it is 5.0 and 5.7 percent. For firms that occupy shops, external returns are somewhat more important: the expenditure on agglomeration is 7.9 percent of the expenditure on floor space.

The control variables have in general plausible signs. Shops are substantially more expensive. Renovated and newly constructed buildings are respectively about 7.5 and 15 percent more expensive. Buildings that are taller than 80 meters are about 15 percent more expensive, confirming the presence of a substantial landmark effect (see Chapter 4). Listed buildings are 8.6 percent less expensive, as it is often not allowed to adjust the interior and exterior of a building. Buildings in conservation areas are 11.5 percent more expensive, suggesting that there is a positive effect associated with the presence of historic amenities. Buildings near highways are 11.4 percent more expensive, as these locations are so-called sight-locations and usually are well accessible by car.

B. *Sensitivity analysis*

In this subsection we present a robustness analysis of the parametric regressions. Table 2.2 summarises the results. In Specification (3) we exclude control variables except for year dummies to test whether there is local correlation with omitted variables. It is observed that the effect of agglomeration is now

TABLE 2.2 — ROBUSTNESS ANALYSIS OF REGRESSION RESULTS
(Dependent variable: the logarithm of yearly rent)

	(3)	(4)	(5)	(6)	(7)	(8)
Agglomeration *(log)*	0.073	0.073	0.133	0.043	0.041	
	(0.011) ***	(0.018) ***	(0.019) ***	(0.019) **	(0.015) *	
Agglomeration in own sector *(log)*						0.055
						(0.015) ***
Population *(log)*					0.016	
					(0.017)	
Size office *(log)*	0.893	0.999	0.998	0.999	0.998	1.000
	(0.009) ***	(0.007) ***	(0.006) ***	(0.010) ***	(0.006) ***	(0.006) ***
Size shop *(log)*	0.949	0.645	0.645	0.644	0.648	0.646
	(0.011) ***	(0.021) ***	(0.021) ***	(0.039) ***	(0.021) ***	(0.021) ***
Size industrial building *(log)*	0.785	0.889	0.883	0.906	0.883	0.889
	(0.008) ***	(0.020) ***	(0.020) ***	(0.027) ***	(0.020) ***	(0.020) ***
Control variables included	No	Yes	Yes	Yes	Yes	Yes
Number of observations	2,631	2,631	2,631	1,384	2,631	2,631
R^2			0.907			
F-Test for weak instruments	2381.03	262.274		961.439	969.260	268.899
Test for exogeneity	12.047	0.385		6.194	10.226	0.000
(critical value)	(3.841)	(3.841)		(3.841)	(3.841)	(3.841)
Overidentification test	1.725	0.884		0.116	2.178	2.133
(critical value)	(3.841)	(3.481)		(3.841)	(3.841)	(3.841)

Notes: See Table 2.1. Instrumental variables are used in all specifications, except in (5).

slightly higher: the agglomeration elasticity is 0.073, which is still a reasonable value.[25]

Specification (4) includes two alternative instruments. As a first alternative instrument, we include the logarithm of municipal population in 1870. We also measure whether a location was below water in 1812, so whether the land has been reclaimed. For these areas, employment density was strictly zero in 1812. So, due to autocorrelation in employment density, we may expect that employment density is lower in these areas. According to Specification (4), the effect of agglomeration is now slightly higher, implying that, if anything, our results are conservative. The over-identification test does not indicate that these alternative instruments are invalid. The instruments are however weaker than the instruments used in Specification (2), so we prefer the results of Specification (2).

Similar to Au and Henderson (2006) and Arzaghi and Henderson (2008), as a second informal test for validity, we include the instruments directly in the ordinary least squares regression of rent (see Specification (5)). When agglomeration is correlated with unobserved endowments, the instruments will absorb some of the bias of the current agglomeration effect. So, if the instruments are invalid, the coefficient of agglomeration should *decline*. In Specification (5), however, we observe that the effect of agglomeration is substantially *larger* than in Specification (1). Distance to station in 1870 is statistically significantly correlated with current rents, whereas population density in 1870 is not correlated with rents.

Our sample encompasses a relatively long time-period from 1990-2000. When unobserved (natural) advantages change over time, this may introduce an additional bias in our estimates. Specification (6) therefore only includes transactions from the second half of this period. The effect is slightly lower: the agglomeration elasticity is 0.043. As our sample is almost halved, the standard error is also somewhat higher.

In Specification (7) we include a weighted population measure (using a formula similar to (12)), to test if the positive effect is not caused by nearby population instead of employment. It is observed that the effect of weighted employment is very similar to previous specifications and that population is not significantly positively related to office rents. Notice that we do not instrument population, so that it is likely that this coefficient is overstated and may lead to a downward bias of the effect of agglomeration.[26]

Specification (8) includes another measure of agglomeration, which only takes into account employment in the own sector (again, using a formula similar to (12)).[27] It appears infeasible to estimate an equation with two endogenous variables (agglomeration of all sectors and agglomeration in the own sector, also known as urbanisation and localisation economies), so we estimate an equation where we only include employment density in the own sector. It appears that the effect is very similar to the effect of density in all sectors. This is not too surprising as the partial correlation between the two measures is considerable (0.572). When we do not account for endogeneity and include both measures, the elasticities for agglomeration in all sectors and agglomeration in the own sector are respectively

[25] The elasticity of size in shops is substantially higher compared to other specifications, because we do not include building type dummies.
[26] The partial correlation between population and agglomeration is positive and equal to 0.607.
[27] See for the sectoral classification, Table 2.A2 in the Appendix.

0.046 and 0.038 (in line with 0.083 in (1)), suggesting that both urbanisation and localisation economies are equally important.

We also test the robustness of the effect of agglomeration with respect to the choice of the threshold distance d_T, which is an important parameter in the calculation of the employment density (see equation (2.13)). In Figure 2.A2 in the Appendix, we show that the effect of agglomeration decreases for $0 < d_T < 1.5$, and slightly increases afterwards, probably because less localised Marshallian agglomeration economies (e.g. specialised labour market) become more important over longer distances (see Arzaghi and Henderson, 2008; Jofre-Monseny et al., 2011). All estimated elasticities are between 0.045 and 0.100, so our estimate presented in (2) is most likely conservative.

2.6 Semiparametric regressions

A. First stage results

Table 2.3 summarises the results for the semiparametric regressions.[28] Specification (9) does not control for endogeneity. It is shown that the average estimate is almost identical to the point-estimate in Specification (1).

We observe the same in Specification (10) where we control for endogeneity: the elasticity of agglomeration is 0.051 on average. In Specification (11) we replicate the analysis, but also include an indicator for the age of the firm in the kernel. We do not have data on the exact age of the establishment, but each establishment has a unique ID on the basis of which we create an age index, such that newer firms generally have a lower index value, which we use as an (imperfect) indicator for firm age. We include this age index in the kernel and transform this index with zero mean and unit standard deviation. The average elasticity of agglomeration in Specification (11) is now 0.046, slightly lower than in Specification (10). Specifications (10) and (11) seem to suggest that firms do not value agglomeration. However, the standard error of the average effect is quite large and therefore not very

TABLE 2.3 — SEMIPARAMETRIC REGRESSION RESULTS – FIRST STAGE
(Dependent variable: the logarithm of yearly rent)

	(9)	(10)	(11)
Agglomeration *(log)*	0.081 (0.038)**	0.051 (0.038)	0.046 (0.038)
Size office *(log)*	0.987 (0.031)***	0.988 (0.032)***	0.989 (0.034)***
Size shop *(log)*	0.644 (0.054)***	0.646 (0.055)***	0.653 (0.059)***
Size industrial building *(log)*	0.863 (0.079)***	0.862 (0.078)***	0.861 (0.076)***
Control variables included (17)	Yes	Yes	Yes
Municipality fixed effects (56)	Yes	Yes	Yes
Transaction year dummies (20)	Yes	Yes	Yes
Number of observations	2,631	2,631	2,631
R^2	0.940		

Notes: We present the average of all coefficients. The bootstrapped standard errors (250 replications) are between parentheses. Variables that are included in the kernel are employment, SBI main sector, SBI two-digit sector, SBI three-digit sector and SBI five-digit sector. In Specification (3) we also include an indicator for the age of the firm.

[28] We assume bandwidths of 1.5 for continuous weight variables and 0.3 for categorical weight variables, included in the kernel. We also have experimented with other bandwidths, but changes in the bandwidths will not influence the main results of this analysis.

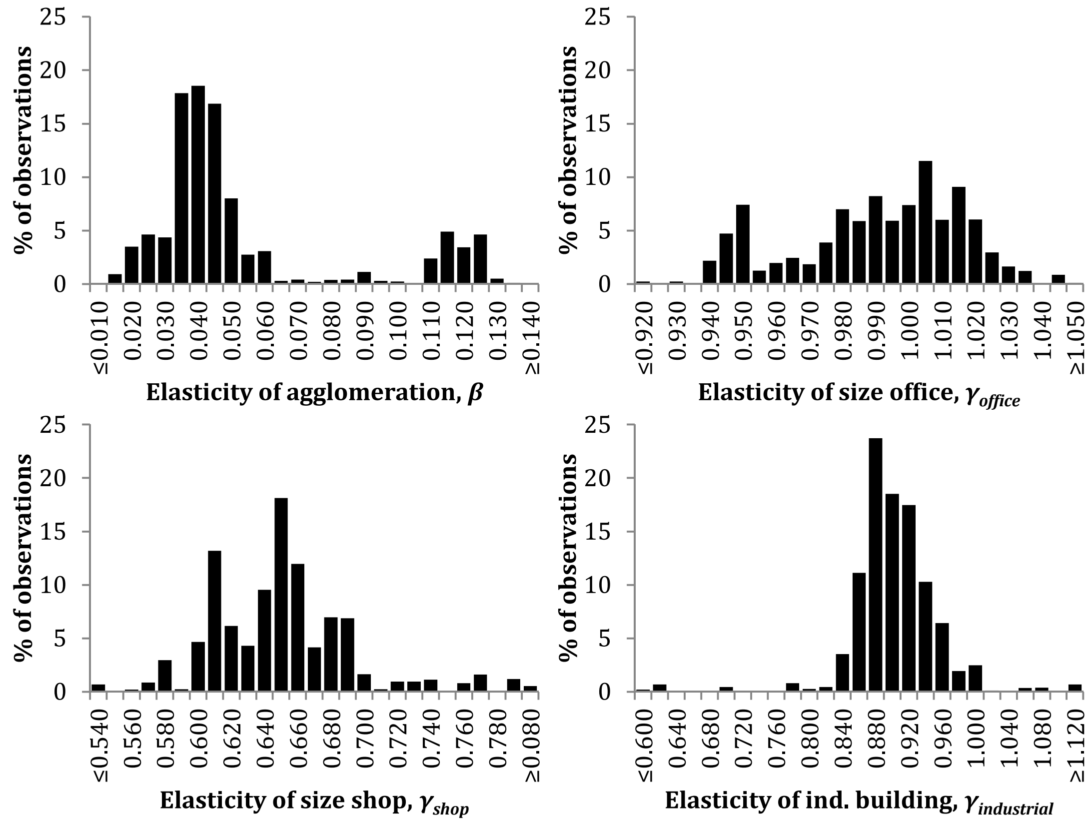

FIGURE 2.1 — DISTRIBUTIONS OF ESTIMATED COEFFICIENTS FOR SPECIFICATION (10)

informative when there is substantial heterogeneity. It appears that agglomeration has a significant impact (at the 5 percent level) in 71 and 55 percent of the firms for respectively Specifications (10) and (11) (for size, the coefficients are always statistically different from 0).

In Figure 2.1, we display histograms of the estimated elasticities for Specification (10). The elasticities of agglomeration are always positive and are between 0.01 and 0.14 in 99 percent of thecases. The distribution is bimodal, so there is a group of firms that spend substantially more on agglomeration. It appears that these are retailers which have on average a substantially higher elasticity of agglomeration (0.107) than other firms (0.038). The elasticity of office space is between 0.94 and 1.05 for 99 percent of firms. So, there is remarkably little heterogeneity in the WTP for an additional square meter of office space. For shop size, we observe somewhat more heterogeneity: 99 percent of the elasticities are between 0.54 and 0.80. The elasticities of industrial buildings are between 0.70 and 1.20 for 99 percent of firms.

B. Second stage results

In Figure 2.2, histograms of the ratios of structural parameters of agglomeration and floor space are presented. Expenditure on agglomeration appears to be limited relative to expenditure on floor space: agglomeration expenditure is on average only 5.3 and 5.7 percent of floor space expenditure for office and industrial buildings. For firms that occupy shops, agglomeration, and therefore external returns to

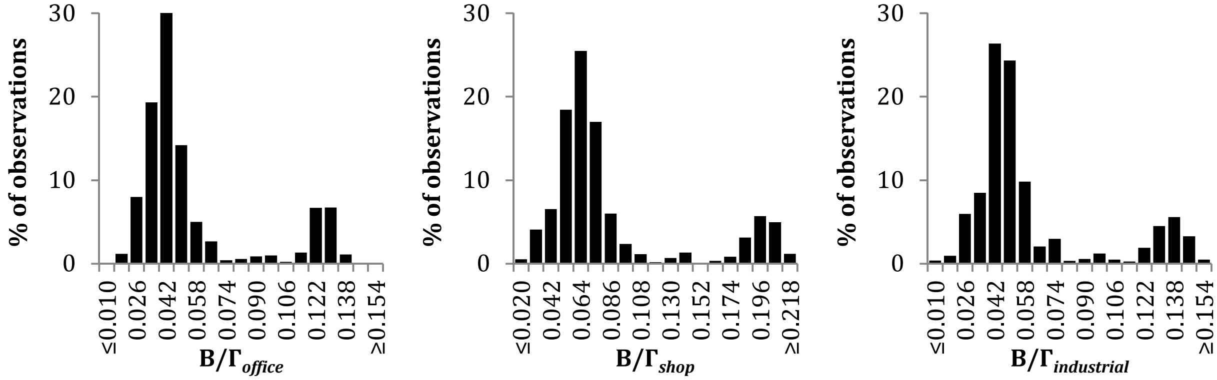

FIGURE 2.2 — DISTRIBUTIONS OF ESTIMATED RATIOS OF COEFFICIENTS

TABLE 2.4 — SEMIPARAMETRIC REGRESSION RESULTS – SECOND STAGE
(Dependent variables: ratios of structural parameters)

	(10-1)		(10-2)		(10-3)	
	$\mathrm{B}/\Gamma_{office}$		B/Γ_{shop}		$\mathrm{B}/\Gamma_{industrial}$	
Employment *(log)*	0.0000	(0.0007)	-0.0018	(0.0011)	-0.0015	(0.0017)
Transport	-0.0087	(0.0027)***	-0.0221	(0.0040)***	-0.0093	(0.0034)***
Wholesale	-0.0007	(0.0023)	0.0015	(0.0035)	-0.0014	(0.0031)
Retail	0.0710	(0.0027)***	0.1693	(0.0042)***	0.0792	(0.0039)***
Hotels and recreation	-0.0018	(0.0037)	-0.0096	(0.0057)*	0.0047	(0.0053)
Business services	-0.0009	(0.0022)	-0.0028	(0.0033)	0.0017	(0.0033)
Government	0.0120	(0.0041)***	0.0274	(0.0059)***	0.0164	(0.0050)***
Education	0.0062	(0.0036)*	0.0124	(0.0049)**	0.0056	(0.0039)
Healthcare	-0.0023	(0.0035)	-0.0058	(0.0053)	-0.0012	(0.0040)
Other	-0.0088	(0.0032)***	-0.0208	(0.0052)***	-0.0095	(0.0042)**
Constant	-0.0140	(0.0028)***	-0.0280	(0.0044)***	-0.0126	(0.0056)**
Number of observations	2,631		2,631		2,631	
R^2	0.754		0.756		0.783	

Notes: 'Manufacturing' is the omitted category. Bootstrapped standard errors (250 replications) are between parentheses.
*** Significant at the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

scale, is relatively more important: on average, expenditure on agglomeration is 8.1 percent of expenditure on floor space. These average estimates are very similar to the expenditure shares calculated from Specification (2). All histograms show bimodal distributions, so the heterogeneity in elasticity of agglomeration seem to dominate the heterogeneity in property size (see also Figure 1).

In Table 2.4, we present the results of the second stage, which are regressions of firm characteristics on ratios of structural parameters.[29] Specifications (10-1), (10-2) and (10-3) show that there is no significant employment effect of employment on the relative productivity of agglomeration. In other

[29] Note that we are able to estimate ratios of parameters for all sectors and building types, as all building types are occupied by firms of each sector (e.g., government organisations also have buildings that are used as shops, such as public employment centres, and industrial buildings to keep gardening tools).

TABLE 2.5 — SEMIPARAMETRIC REGRESSION RESULTS – SECOND STAGE
(Dependent variables: ratios of structural parameters)

	(11-1)		(11-2)		(11-3)	
	$\mathrm{B}/\Gamma_{office}$		B/Γ_{shop}		$\mathrm{B}/\Gamma_{industrial}$	
Employment *(log)*	0.0001	(0.0006)	-0.0009	(0.0008)	-0.0012	(0.0006)**
Age index (*std*)	-0.0012	(0.0005)**	-0.0029	(0.0008)***	-0.0009	(0.0005)*
Transport	-0.0085	(0.0030)***	-0.0134	(0.0044)***	-0.0083	(0.0032)***
Wholesale	-0.0015	(0.0022)	-0.0008	(0.0033)	-0.0019	(0.0024)
Retail	0.0716	(0.0027)***	0.1087	(0.0039)***	0.0767	(0.0028)***
Hotels and recreation	-0.0010	(0.0037)	-0.0032	(0.0057)	0.0047	(0.0045)
Business services	-0.0015	(0.0019)	-0.0024	(0.0027)	0.0008	(0.0021)
Government	0.0130	(0.0040)***	0.0188	(0.0056)***	0.0163	(0.0038)***
Education	0.0076	(0.0033)**	0.0098	(0.0045)**	0.0073	(0.0032)**
Healthcare	-0.0014	(0.0037)	-0.0024	(0.0055)	-0.0002	(0.0041)
Other	-0.0112	(0.0036)***	-0.0161	(0.0057)***	-0.0117	(0.0040)***
Constant	-0.0140	(0.0025)***	-0.0184	(0.0035)***	-0.0125	(0.0027)***
Number of observations	2,631		2,631		2,631	
R^2	0.739		0.752		0.764	

Notes: See Table 2.4.

words, large firms do not differ from small firms in their expenditure on agglomeration relative to property size. Retailers have a relatively strong preference for agglomeration: expenditure on agglomeration relative to property size is 7.1 to 16.9 percentage points higher than manufacturing firms. Retailers are likely to prefer relatively small buildings in dense urban areas, because there may exists localisation economies, so by allowing customers to go to a shop nearby (Eberts and McMillen, 1999).[30] It is also observed that the public sector prefer dense locations, as the expenditure is 1.2 to 2.7 percentage points higher than a manufacturing firm. An explanation is that (local) governments are less flexible in their location choice. For example, local governments of Rotterdam have to locate in the relatively expensive city centre of Rotterdam and cannot locate in the periphery, forcing them to outbid other firms on these locations. Furthermore, it is shown that firms in the transport sector are relatively less productive in dense urban areas, possibly because dense areas imply traffic congestion, which is particularly costly for this sector.

The second stage results of Specification (11) which includes the age index are presented in Table 2.5. The age index has a negative significant impact in all specifications. Although the magnitude of this effect is difficult to determine, it shows that younger firms prefer dense urban areas. This is consistent with Henderson et al. (1995) and Duranton and Puga (2001) who show that younger firms tend to prefer dense diverse areas, whereas more mature firms are relatively more productive in specialised, low-cost and low-density locations (see also Neffke et al. 2011). Other coefficients are very similar to

[30] It may be argued that retailers do not prefer dense employment areas, but densely *populated* areas, as this likely lead to a sufficient number of customers. When we control for population (similar to Specification (7)), the coefficients of "Retail" are reduced by about 50 percent. Still, retailers have a relatively strong preference to locate in areas with high employment densities. It is not too surprising that we find that retailers also have a relatively strong preference to locate in densely populated areas.

those presented in Table 2.4.[31] The only exception is that these results suggest that larger firms that use industrial buildings prefer less agglomerated areas.

2.7 Conclusions

In this chapter, we consider identification of firm-specific production functions based on commercial property prices. Our identification strategy is in the spirit of Bajari and Benkard (2005) and Bajari and Kahn (2005) that consider consumer markets. We show that one can identify ratios of firm-specific production parameters using a semiparametric control function approach that corrects for endogeneity. In our application, we use unique micro-data of properties' attributes as well as of firm characteristics to estimate the effect of spatial density on rents of commercial buildings and link these to structural parameters of the production function.

We use a two-stage estimation approach. In the first stage we estimate a (reduced-form) semiparametric hedonic price function, where the estimated elasticities with respect to agglomeration and workforce size are firm-specific. In the second stage, given a generalised Cobb-Douglas production function, we identify ratios of firm-specific *structural* production parameters, and therefore the ratios of the expenditure on input variables. The analysis of ratios of structural parameters has the advantage that relatively modest functional form assumptions on the hedonic price function and production function are required and, more important, multi-dimensional hedonic models with many attributes and firm characteristics can be analysed.

It is shown that agglomeration has a positive effect on commercial property rents, revealing the presence of external economies. The results show that the agglomeration elasticity of the rent is about 0.05, so a doubling of agglomeration levels leads to an increase in the average willingness to pay of about 3.5 percent of the rent. This is in line with Arzaghi and Henderson (2008) and Drennan and Kelly (2011) who confine their analysis to firms occupying office buildings. Importantly, the agglomeration elasticity of the rent is positive for all firms. Our estimates show that this elasticity is less than 0.08 for almost all organisations, except for retail firms that usually have a much higher elasticity.

A structural interpretation of our results suggests that firms' expenditure on agglomeration is limited relative to expenditure on floor space. For example, it is on average only 5.3 percent of expenditure on office space. This conclusion does not hold for retail firms: average expenditure on agglomeration is about 20 percent of expenditure on shop floor space. So, shops are likely to be relatively more productive in dense areas due to external returns to scale. It is also found that public sector organisations spend relatively more on agglomeration than most other organisations.

In the next Chapter, we will pay more attention to identification of agglomeration economies. In this Chapter we used historic long-lagged instruments to identify the causal impact of agglomeration on commercial rents. In the next Chapter we will test the key identifying assumption that unobserved endowments that were important long ago are not important anymore today using temporal variation in densities.

---

[31] One may notice that the R^2's of the different specifications are not necessarily higher than in Table 2.4, although we include the age index. This is because we assumed in the first stage of Specification (10) that heterogeneity is only caused by sector and firm size.

Appendix 2.A Descriptives and other results

TABLE 2.A1 — DESCRIPTIVE STATISTICS OF ATTRIBUTES OF RENTAL PROPERTIES

	Mean	Std.Dev.	Min	Max
Price *(in €)*	131,085.681	207,563.220	5,445.000	2,198,565.000
Agglomeration *(<2,500m)*	31,586.233	27,940.228	554.151	92,734.514
Size *(in m^2)*	1,184.908	1,748.825	22.000	19,000.000
Size office *(in m^2)*	1,074.615	1,808.327	65.000	19,000.000
Size shop *(in m^2)*	400.129	701.516	22.000	10,500.000
Size industrial building *(in m^2)*	790.559	1,247.294	80.000	16,700.000
Office building	0.587			
Shop	0.243			
Industrial building	0.170			
Renovated building	0.032			
Newly constructed building	0.126			
Building height >80m	0.015			
Listed building	0.032			
Sale and lease back	0.005			
Rent turnkey	0.015			
Parking spaces	18.588	23.033	1.000	162.000
Parking spaces – missing	0.935			
Road <150m	0.785			
Highway <150m	0.059			
Railway <150m	0.104			
Open Space <500m	0.118			
Water <150m	0.291			
Station <250m	0.051			
Conservation area	0.173			
Population density 1870	2,891.284	4,505.749	37.917	22,482.337
Distance to station 1870 *(in km)*	3.300	3.618	0.041	21.387
Transaction year	1,999.280	4.472	1,990.000	2,010.000
Number of Observations		2,631		

TABLE 2.A2 — DESCRIPTIVE STATISTICS OF FIRM CHARACTERISTICS

	Mean	Std.Dev.	Min	Max
Employment	67.401	198.049	1.000	3,000.000
Firm age index	-256,302,217.412	200,880,697.426	-708,096,418.000	-2,220.000
Manufacturing	0.076	0.264	0.000	1.000
Transport	0.048	0.214	0.000	1.000
Wholesale	0.143	0.350	0.000	1.000
Retail	0.203	0.403	0.000	1.000
Hotels and recreation	0.034	0.182	0.000	1.000
Business services	0.377	0.485	0.000	1.000
Government	0.031	0.173	0.000	1.000
Healthcare	0.052	0.221	0.000	1.000
Education	0.016	0.125	0.000	1.000
Other	0.020	0.141	0.000	1.000
Number of observations		2,631		

FIGURE 2.A1 — MAP OF AGGLOMERATION LEVELS IN SOUTH-HOLLAND FOR $d_T = 2.5$

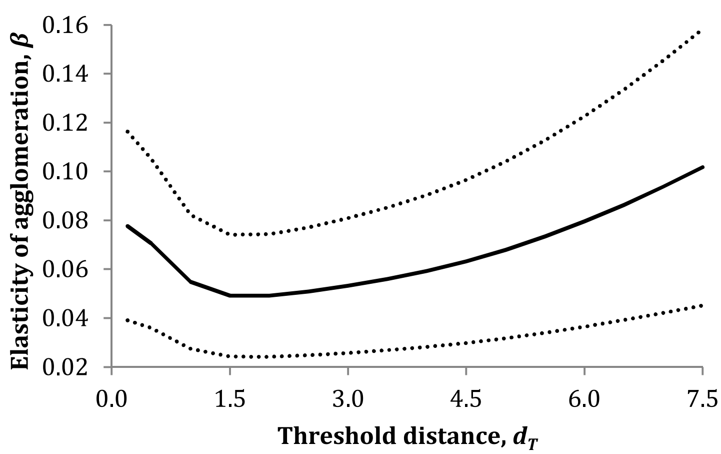

FIGURE 2.A2 — ELASTICITY WITH RESPECT TO AGGLOMERATION FOR DIFFERENT d_T